

**A STUDY OF ARIMA AND GARCH MODELS
TO FORECAST CRUDE PALM OIL (CPO) EXPORT IN INDONESIA**

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Abstract

Indonesia is the biggest exporter Crude Palm Oil (CPO) country in the world. In 2013, export of Indonesian CPO reach \$ 15.84 billion. CPO is important for various things, such as cooking oil, vegetable fat for milk and ice cream, raw materials of soap or cosmetics industry, or alternative fuels. The export of CPO is very important for the national economic development since it contributed significantly to the trade balance of Indonesia. Therefore, in order to support the government in making the right policy, forecasting export of CPO is necessary.

In this study, a series of CPO export data was analyzed using time series analysis and forecasting techniques. Two classes of models were investigated, namely ARIMA models and GARCH models, and the comparison of the models was reviewed. The data used in this study were monthly export registration data, available at various ports for export across Indonesia from 1996 to 2013.

The results showed that the first model was suitable for time series data with constant variance and hence if the problem of variance heterogeneity existed in the data, then a transformation to the data was required. The second model, on the other hand, was suitable for time series data having serious problems with heterogeneity of variance. However, in this study it was shown that a simple transformation of ARIMA models has fitted the data properly and could overcome the heterogeneity of variance problems.

Key words: CPO, ARIMA, log transformation, GARCH, forecasting

INTRODUCTION

Indonesia is the biggest country in the world in exporting Crude Palm Oil (CPO). In 2013, Indonesian exports of CPO reach \$ 15.84 billion. This value was higher than Malaysian exports of CPO which is up to \$ 12.31 billion and Netherland export of CPO which is amounted to \$ 1.53 billion (www.comtrade.un.org).

Demand of CPO from all countries in the world is increase every year. This increasing demand is influenced by CPO benefits. The benefits of CPO are for raw materials of food such as cooking oil, vegetable fat for milk and ice cream; for raw materials of soap or cosmetics industry; and for alternative fuels. According to Statistics Indonesia (BPS), in 2013, Indonesian CPO mostly exported to India up to \$ 4.28 billion. Beside that, Indonesian CPO also exported to other countries such as China amounted to \$ 1.79 billion, Netherland \$ 1.03 billion, Pakistan \$ 0.81 billion, Italy \$ 0.79 billion and Singapore \$ 0.65 billion.

Based on those two condition, export of CPO is very important for Indonesian economic development. It because, export CPO contributed significantly to the trade balance. The contribution of Indonesian CPO exports to the Indonesian total exports reached 8.68 percent, after coal (13.42 percent) and natural gas (9.93 percent). Beside it contribution, the importance of export CPO for economic development are improving society welfare and increasing foreign exchange. Therefore, in order to support the government in making the right policy, forecasting export of CPO is necessary.

In this study, a series of CPO export data was analyzed using time series analysis and forecasting techniques. Time series analysis is to obtain a model that fit with the observed time series and subsequent use as a series forecasting model for the future. Two classes of models were investigated, namely ARIMA models and GARCH models, and the comparison of the models was reviewed.

The formulation of the problem is approached with two questions that will be answered in this research. First, which model can provide the best forecasting between ARIMA and GARCH models? Second, how is the value of Indonesian CPO exports growth in the next period?

The purpose of this research is divided into three parts. The first purpose is to build and to study the equations models of Indonesian CPO export value. The second purpose is to determine the best model for Indonesian CPO export value. The third purpose is to forecast the value of Indonesian CPO exports.

LITERATURE REVIEW

Export

Exports in general trade system is in use when the statistical territory of a country coincides with its economic territory. Consequently, under the general trade system, exports include all goods leaving the economic territory of a compiling country. In this case the goods include commercial goods, non-commercial goods (grants, donations, gifts), moving goods (ship, aircraft, satellite) and also goods that processed abroad and the production are re-export to origin (United Nation, 1998).

Crude Palm Oil (CPO)

Crude Palm Oil (CPO) is an oil that derived from palm oil processing. It produced by boiling and extorting pulp or mesocarp of coconut palm. Beside CPO, there is other types of palm oil which is called Palm Kernel Oil (PKO). PKO is an oil that derived from the nucleus of palm kernel. (Hariyadi, 2008).

ARIMA Models

The Autoregressive Integrated Moving Average (ARIMA) models are often known by Box-Jenkins models. Box-Jenkins models consist of several models, namely: Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA). ARIMA model is ARMA model which is not stationary. To make a stationary data, it is necessary to make a differencing data process. A time series Y_t is said to follow an integrated autoregressive moving average model if the d th differenced $W_t = \nabla^d Y_t$ is a stationary ARMA process. If W_t follows an ARMA (p,q) model, we say that Y_t is an ARIMA(p,d,q) process (Cryer, 2008). The general form of ARIMA (p,d,q) is

$$\phi(B)(1-B)^d Y_t = \theta(B)e_t \quad (1)$$

B is the backshift operator, $BY_t = Y_{t-1}$ and $(1-B)^d = \nabla^d$; ϕ is parameter of autoregressive; θ is parameter of moving average; e_t is an error. In the constant terms of ARIMA models, with a nonzero constant mean μ , the formulation of ARIMA(p,d,q) is

$$W_t - \mu = \phi_1(W_{t-1} - \mu) + \phi_2(W_{t-2} - \mu) + \dots + \phi_p(W_{t-p} - \mu) + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} \dots - \theta_q e_{t-q} \quad (2)$$

GARCH Models

Regression and ARIMA modeling assumes that the variance of error is constant for all observations. When an error has non-constant variance, the data have heteroscedasticity problems. This problem can cause the estimation to becomes inefficient, unless it is possible to perform transformations that can be made into a homogeneous variety. Some models can be used to solve a non-homogeneous variance problems, such as: Auto regressive Conditional Heteroscedasticity (ARCH) model. ARCH (q) model is the process of 'short memory' that just

qth latest squared residual are used to predict changes in the value of diversity. In addition to the ARCH model, GARCH model is used to process 'long memory' which uses the entire squared residual to estimate the variance. Referring to Bollerslev, 1986, the general form of the GARCH model (p, q) is

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^p \beta_i \sigma_{t-i}^2 + \sum_{j=1}^q \alpha_j \epsilon_{t-j}^2 \quad (3)$$

σ_t^2 is a variance; α_0 is a constant; β_i is parameter of GARCH, $i=1,2, \dots, p$; ϵ_t^2 is squared residual; α_j is parameter of ARCH, $j=1,2, \dots, q$. By using the backshift operator B, which is defined as $B\epsilon_t = \epsilon_{t-1}$, the model (3) becomes

$$\sigma_t^2 = \alpha_0 + \beta(B)\sigma_t^2 + \alpha(B)\epsilon_t^2 \quad (4)$$

RESEARCH METHOD

Data

This research use monthly data of Indonesian CPO exports value that obtained from Statistics Indonesia (BPS). The monthly data series are begining from 1996 to 2013, so there are 216 series of observational data. The unit of the data series is in \$ (US dollars).

Research Methodology

Variable that used in this research is the value of Indonesian CPO exports variable as Y_t , with t is the monthly periods, $t = 1,2,3, \dots, 216$.

Analysis step in this research are:

1. Exploration of the Indonesian CPO export value data
2. Building and studying the ARIMA model, with the following steps:

- a. Model identification

This step is needed to determine the value of p, d, and q tentative models. The value of p, d, and q is a value that is specified when the data is stationary. The method that is use to determine stationarity are:

- i. Plot the time series data
- ii. Compute and examine the Autocorrelation Function (ACF) and the Partial Autocorrelatin Functin (PACF)

The autocovariances and autocorrelations are useful tools in the Box-Jenkins approach to identifying and estimating time series models (Enders, 2004). The ACF explains how much correlation data sequentially in time series between Y_t and Y_{t+k} . ACF is a comparison between covariance ($\text{cov}(Y_t, Y_{t+k})$) and variance ($\text{var}(Y_t) = \text{var}(Y_{t+k})$) at k time lags. The PACF is a correlation between Y_t and Y_{t+k} after their mutual linear dependency on the intervening variables $Y_{t+1}, Y_{t+2}, \dots, Y_{t+k-1}$ has been removed. If the ACF plot showed slowly down, the data series is not stationary, but if the ACF plot showed cuts off, the data series is stationary.

- iii. Augmented Dickey Fuller test (ADF test)

The null hypothesis is that the data series is not stationary and the alternative hypothesis is that the data series is stationary. If the absolute value of the ADF statistic is greater than the critical value, then the data series is stationary.

- b. Parameter estimation

After getting the value of p, d, and q and tentative models, the next step is to estimate the parameters of the ARIMA model. The estimation method is using the Ordinary Least Square Estimation. The parameter estimation of the least squares method is a statistic that has a minimum sum square errors.

- c. Model selection

The best model is a model that has a smallest value of Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC). The formula to calculate the AIC and SBC are:

$$AIC(M) = -2 \ln(\text{maximum likelihood}) + 2M, \text{ and}$$

$$SBC(M) = -2 \ln(\text{maximum likelihood}) + M \ln n.$$

M is the number of model parameters and n is the number of observations (Wei, 2006).

d. Overfitting

Overfitting is one way to fit the model of the examination of a more general model of tentative models. Tentative models will be selected to continue to be used when additional parameters are not significantly different from zero and other parameter estimation did not differ from those obtained in the tentative models.

e. Diagnostic checking

After getting the estimators of ARIMA model, further examination of the model is associated with the model prediction capabilities through residual analysis. There are three things that need to be examined from a residual:

- i. normality test, by examining plot of data and statistical tests of Jarque-Bera,
- ii. white noise process, by examining plot of ACF and PACF, and statistical tests of Ljung-Box (Q-statistic). This is an approximate statistical test of the hypothesis that none of the autocorrelations of the series up to a given lag are significantly different from zero,
- iii. homogeneity of variance test, using statistical ARCH test (ARCH-Lagrange Multiplier).

3. Log transformations

If the time series data is not stationary in the variance, the transformation is needed to overcome this problem. The logarithmic transformation will be used to make the homogeneous variance. The first step is to create the logarithmic data of Indonesian CPO export value, then to build the ARIMA model with the same procedure in the second step.

4. Building and studying GARCH model, with the following steps:

a. Determinating of the order GARCH

If the Lagrange Multiplier Test for residual data is significant at slightly earlier lags then the models is ARCH model. But, if the LM test is significant at a lot of lags, then the model is GARCH model. The determination of the order of GARCH is starting from the smallest order GARCH (1,1).

b. Parameter estimation

To estimate the parameter of GARCH model, the Maximum Likelihood Estimation is used.

c. Overfitting, to order the model is required to obtain a more appropriate model.

d. Diagnostic of the model, using a residual:

- i. Residual homogeneity tests, and
- ii. Residual normality tests.

5. Model selection based on forecast errors

The best model is a model that has a smallest value of Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The formula to calculate the MAE and MAPE are: $MAE = \frac{1}{M} \sum_{l=1}^M |e_l|$ and $MAPE = \left(\frac{1}{M} \sum_{l=1}^M \left| \frac{e_l}{Y_{n+l}} \right| \right) 100\%$ (Wei, 2006). n is the forecast origin larger than or equal to the length of the series and l is the forecasting periods.

6. Forecasting

After getting the appropriate model, forecasting in Indonesian CPO export value for 24 periods ahead will be done.

RESULT AND DISCUSSION

Exploration of Indonesian CPO Export Value Data

There were 216 monthly observational data of Indonesian CPO export value from 1996 to 2013. Figure 1 is a plot between the Indonesian CPO export value to the periods.

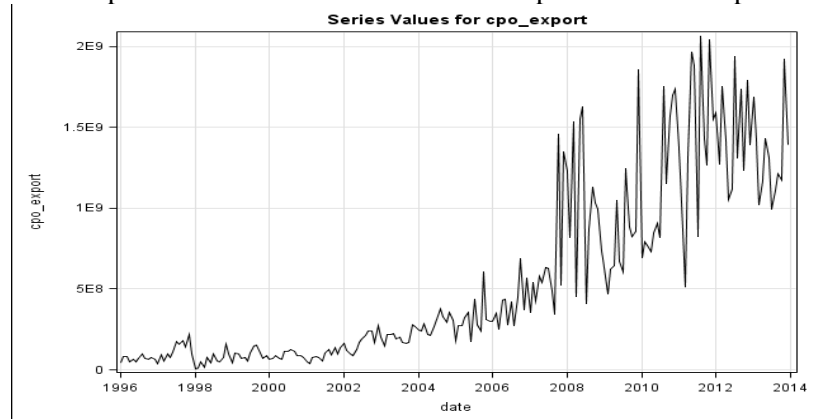


Figure 1. Data Plot of Indonesian CPO Export Value In 1996-2013

Generally, growth of monthly Indonesian CPO export value from 1996 to 2013 is increase, but it is fluctuating. From the data plot above, shows that the Indonesian CPO export value data do not indicate a seasonal pattern. CPO export value was highest in August 2011 about \$ 2,063,660,646. While the lowest CPO export value was in January 1998 about \$ 5,092,621.

Building and studying the ARIMA model

ARIMA model is the equations model in time series analysis that used if the observational data was not stationary in mean. From the data plot of Indonesian CPO export value in Figure 1 above, it show that the average of Indonesian CPO export data is not constant, so that the data of Indonesian CPO export value have not stationary.

To solve the non stationary data, differencing process is needed. The result of Indonesian CPO export value data plot with first differences is in Figure 2:

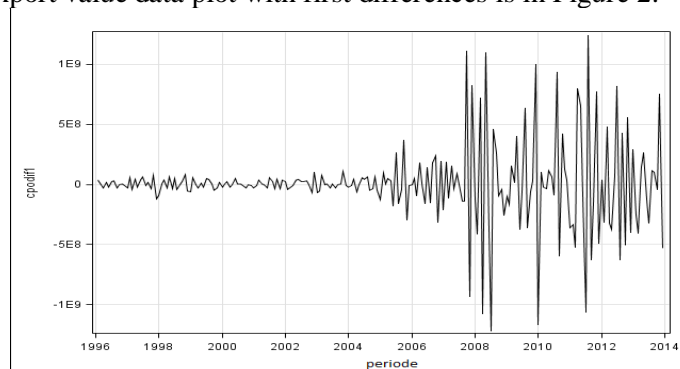


Figure 2. Data Plot of Indonesian CPO Export Value With First Difference

From the data plot above, it show that the data of Indonesian CPO export value are stationary with the constant average of the first difference Indonesian CPO export data.

Besides using data plot, stationary data can be seen with ACF and PCF plot. From ACF plot, the correlation of Indonesian CPO export value is significant in lag 1. This condition can be seen in Figure 3 below. From figure 3, the correlation value is not decreasing slowly or ACF plot is a cuts off. It's mean that the data is already stationary. In the other side, stationary data by using PACF plot is significant at first lag to forth lag.

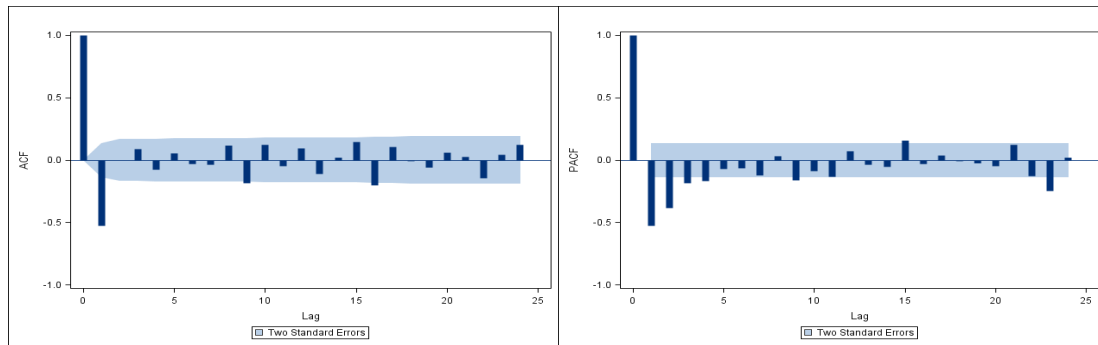


Figure 3. The ACF and PACF Plot of Indonesian CPO Export Value with First Difference

To make sure that the Indonesian CPO export value data is stationary, we use the Augmented Dickey Fuller (ADF) test. The result of this test in monthly data of Indonesian CPO Export Value can be seen in Table 1.

Table 1. ADF Test of Indonesian CPO Export Value Data with First Difference

Type	Lags	t-Statistic	p-Value
<i>Zero Mean</i>	1	-18.9616	.0000
	12	-5.22645	.0000
<i>Single Mean</i>	1	-18.9645	.0000
	12	-5.53051	.0000
<i>Trend</i>	1	-18.9378	.0000
	12	-5.58423	.0000

Table 1 show that the probability of all type of equation data (zero mean, single mean, and trend) in lag 1 and 12, is less than 5% alpha. Its mean that the null hypothesis is rejected and the data is stationary.

After Indonesian CPO export value data with first differences already stationary, the next step is to get the value of p, d, and q to identification ARIMA(p,d,q) models. ACF and PACF plot value of Indonesian CPO exports with first differences, obtained some tentative ARIMA model, they are ARIMA (0,1,1), ARIMA (4,1,0) and ARIMA (4,1,1). After getting 3 tentative ARIMA model, the parameters will be estimated by ordinary least square method. Table 2 below shows the summary of the tentative ARIMA model parameter estimation.

Table 2. Parameter Estimation of Tentative ARIMA Model

No	ARIMA Model	Parameter	AIC	SBC	Estimate	p-value
1	ARIMA(0,1,1)	C	41.49806	41.52941	6281108	.0428
		MA(1)			-0.821410	.0000
2	ARIMA(4,1,0)	C	41.56466	41.64408	6284750	.2930
		AR(1)			-0.830822	.0000
		AR(2)			-0.610901	.0000
		AR(3)			-0.319270	.0004
		AR(4)			-0.169153	.0168
3	ARIMA(4,1,1)	C	41.53976	41.63508	6759354	.0137
		AR(1)			0.015584	.8719
		AR(2)			0.085373	.3719
		AR(3)			0.155315	.0819
		AR(4)			0.029685	.7139
		MA(1)			-0.892377	.0000

From the 3 tentative ARIMA model above, the first equation is the best, because the value of AIC and SBC showed the smallest values and the parameter estimation is significant, that can

be seen from the p-value that less than 5% alpha. In the second equation, the parameter estimation is also significant, but the AIC and SBC values are greater than the first equation. While in the third equation, there is only one significant parameters estimation and the values of AIC and SBC is still greater than the first equation. So that, the best model is the ARIMA (0,1,1).

Overfitting is one way to check the model by fitting a model that is more common than tentative models. Overfitting of the ARIMA(0,1,1) will be performed with ARIMA (0,1,2) and ARIMA (1,1,1). The results of parameter estimation show that the ARIMA (0,1,1) remains the best model, because the parameter estimation in other models are not significant and its value of AIC and SBC are greater than the first model. So, the ARIMA(0,1,1) model is $Y_t = 6281108 + 0.821410e_{t-1} + e_t$.

After getting the ARIMA (0,1,1) as the best model, the next step is to analyze the residuals, includes examining normality, residuals white noise process, and homogeneity of variance. Normality examination is done by looking at residual plots and statistical tests Jarque-Bera. Figure 4 showed the histogram and the value of the Jarque-Bera statistics. From the histogram, it appears that the histogram does not resemble a symmetrical bell shape, which means that the residual is not the normal distribution. P-values Jarque-Bera statistic is less than 5% alpha, which also means that the residual is not the normal distribution.

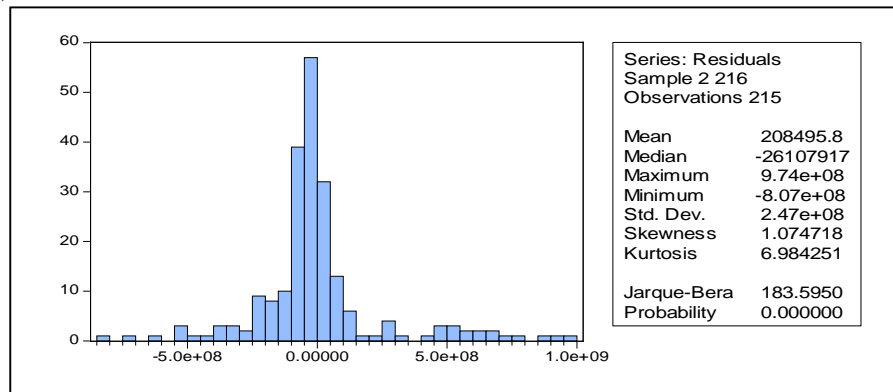


Figure 4. Plot of Residual Normality and Jarque-Bera Statistics Tests

To see the diagnostic of residuals white noise process, Ljung-Box Test Statistics (Q-statistic) are used. The test results showed that some of Ljung-Box statistic value at large lags are significant, so the residual is not a white noise process at large lags.

Table 3. The Results of Ljung-Box Test Statistics on Residual ARIMA (0,1,1)

Lags	1	6	12	18	24	30	36
ACF	-.054	-.04	.091	-.05	.139	-.042	.074
PACF	-.054	-.047	.123	-.076	.198	.021	.163
Q-Stat	.6297	3.3514	11.828	21.544	36.848	48.802	63.223
Prob.		.646	.377	.203	.034	.012	.002

To see the diagnostic of residuals variance homogeneity, it can be determined by ARCH-Lagrange Multiplier test. The results of ARCH-LM test are shown in Table 4:

Table 4. The Results of ARCH-LM Statistics Tests on Residual ARIMA (0,1,1)

Lags	F-statistic	Obs*R-squared	Prob. F	Prob. Chi-Square
1	11.55459	11.06075	.0008	.0009
3	13.78602	35.16192	.0000	.0000
5	8.588122	36.51699	.0000	.0000

From Table 4 above, it can be seen that the p-value for the Chi-Square on all the lag is smaller than 5% alpha, so the residuals variance is not homogeneous.

Log transformations

The ARIMA (0,1,1) obtained is still having variance heterogeneity problems, so the log transformation method will be performed on the data to overcome that problems and the new ARIMA model will be built. Data plots of log Indonesian CPO export value indicate that the data are not stationary. Likewise from the ACF plot looks down slowly, indicates that the data is not stationary.

The differencing process is used to overcome nonstationary of this data. The data plot, ACF plot, and PACF plot indicate that the log CPO export value data with first differences are already stationary. Using the ADF statistic test, the results also indicate that the log CPO export value data with first differences are already stationary. From the ACF plot and PACF plot, it can be seen that the ACF plot at first lag is significant, whereas the PACF plot at first lag and second lag are significant. So the tentative ARIMA (p,d,q) model are ARIMA (0,1,1), ARIMA (2,1,0) and ARIMA (2,1,1). From the three tentative ARIMA model, it can be seen that the ARIMA(2,1,1) is the best ARIMA model, because the value of AIC and SBC are smaller than others and the parameter estimation is significant.

Overfitting the ARIMA (2,1,1) will be compared with ARIMA (3,1,1) and ARIMA (2,1,2). The parameter estimation results are shown that from the three ARIMA models, only the ARIMA(2,1,1) that have a significant parameter estimation. So, the ARIMA (2,1,1) is still the best model. The ARIMA(2,1,1) model is

$$\text{Log } Y_t = 0.017890 + 0.347755 \text{Log } Y_{t-1} + 0.142758 \text{Log } Y_{t-2} + 0.989811 e_{t-1} + e_t.$$

By looking at the residual plots and statistical tests Jarque-Bera, it can be show that the residual is not the normal distribution. The results of Ljung-Box statistical tests show that, the residuals is a white noise process. The ARCH-LM statistical tests show that the p-value for the Chi-Square on all lag is greater than 5% alpha, so the residual variance is homogenous.

Building and studying the GARCH model

In the previous discussion, Model ARIMA (0,1,1) of the value of Indonesia's CPO export data has a heterogeneity of variance problem. By using a log transformation on the value of Indonesian CPO export data, heterogeneity of variance problem can be solved and obtained ARIMA (2,1,1). In this discussion, we will use the GARCH model to solve the heterogeneity of variance problem in ARIMA (0,1,1) model.

The first step is determining the order of the GARCH model. The determination of the order GARCH is starting from the smallest order, GARCH (1,1). The parameter estimation of GARCH (1,1) is used the maximum likelihood method. It showed that all parameter estimation are significant, so the GARCH (1,1) can be used. Overfitting is done to get a better GARCH model, namely with GARCH (1,2) and GARCH (2,1). In the second equation, all parameter estimation are significant, but the value of AIC and SBC are greater than the first equation. In the third equation, it appears that there is a parameter coefficient that not significant at the 5% alpha and AIC and SBC values are greater than the first equation. So, GARCH (1,1) model is the best model because it has the value of the smallest AIC and SBC. The GARCH(1,1) model is $\sigma_t^2 = (5.82 \times 10^{12}) + 0.855671 \sigma_{t-1}^2 + 0.229671 \epsilon_{t-1}^2$.

The examination of variance heterogeneity in the GARCH (1,1) is using the ARCH-LM statistic test. The results show that at all lags, the p-values for the Chi-Square are greater than alpha 5%, so the residual variance heterogeneity does not occurred. The examination of residual normality can be seen from the histogram and Jarque-Bera statistical tests. The results show that the residual is not a normal distribution.

Model selection base on forecast errors

To determine the best model, it can be seen by comparing the level of accuracy of prediction through MAE and MAPE value between ARIMA (1,1,1) for the log of the value of

Indonesia's CPO export data and GARCH (1,1) Indonesian CPO export value data. The best model is a model that has a smaller value of MAE and MAPE. The results are in table below. It shows that the ARIMA(2,1,1) is better than the GARCH(1,1).

Table 5. The Results of ARCH-LM Statistic Test

Model	MAE	MAPE (%)
ARIMA(2,1,1)	1.62E+08	37.90131
GARCH(1,1)	3.09E+08	69.50711

Forecasting

The forecasting results of ARIMA(2,1,1) for 24 periods ahead are in the table 6:

Table 6. The Results of Forecasting

Periods	Forecasting	Periods	Forecasting
Jan-14	1,932,722,578.49	Jan-15	2,395,555,526.79
Feb-14	1,967,611,023.46	Feb-15	2,438,798,777.58
Mar-14	2,003,129,255.45	Mar-15	2,482,822,631.75
Apr-14	2,039,288,643.03	Apr-15	2,527,641,180.32
May-14	2,076,100,759.99	May-15	2,573,268,768.68
Jun-14	2,113,577,389.03	Jun-15	2,619,720,001.17
Jul-14	2,151,730,525.57	Jul-15	2,667,009,745.76
Aug-14	2,190,572,381.54	Aug-15	2,715,153,138.81
Sep-14	2,230,115,389.34	Sep-15	2,764,165,589.91
Oct-14	2,270,372,205.76	Oct-15	2,814,062,786.82
Nov-14	2,311,355,716.09	Nov-15	2,864,860,700.48
Dec-14	2,353,079,038.21	Dec-15	2,916,575,590.15

From the table above, it can be seen that the results of forecasting are increase at 24 periods ahead.

CONCLUSION

The problems of heterogeneity on ARIMA(0,1,1) of Indonesian CPO export value data can be solved with 2 methods. The first method is aARIMA model with a log transformation and the second is GARCH model. In the first method, the model that be built is more parsimonious than the second. Besides that, on the first method, the forecasting accuracy is better than the second. Both methods produce a homogeneous variance, but the second is better than the first. So, it can be concluded that ARIMA model is better than GARCH models. Based on the forecasting results, the future of Indonesian CPO export value will be better than present.

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